PREDICTING TREE GRADES USING TREE- AND STAND- LEVEL DATA

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Abstract: Log prices can vary significantly by grade, with grade 1 logs often many times the value of grade 3 logs. Because log grades and tree grades are closely linked, a model that predicts tree grades based on tree and stand variables might be useful for predicting stand values. The model could then be used in modeling aggregate supply or in economic optimization. I estimated grade models for ten groups of species found in the southern Appalachians. Data on several thousand trees and stands were acquired from the USDA Forest Service's Eastwide Database. Four measures of data fitness were described and applied to the models estimated. These measures indicated that the models did better at predicting than naive alternatives (e.g., using sample proportions). Substantial unexplained variation, however, remained, and this fact raises some methodological issues regarding maximum likelihood estimation and the efficacy of predicting tree grades.

Introduction

Timber markets are difficult to evaluate because of the influence of log species and grade on stand value. In the southern Appalachians, prices for number 1 grade logs can be six times prices for number 3 grade logs. This range in value reflects a wide variety of end uses, with one implication being that typical aggregate market analysis can be difficult or meaningless. However, while aggregate production quantities hold little meaning, there is no available source of information on timber production by grade. This paper describes one method for estimating the tree grades using standard inventory data. Because tree grades and resulting log grades are closely linked, models of tree grades could help in improving estimates of stand values and the value of timber removals.

The models developed used data from the United States Forest Service's Forest Inventory and Analysis (FIA) Eastwide Database and relates grades of standing timber to tree and stand characteristics that are recorded for removals Because tree grades are discrete and may be considered ordered, an ordered probit model was estimated for each of ten species groups (see Table 1) found in the Southern Appalachian Assessment (SAA) region of the southern Appalachians Results show that the ordered probit method improved the probability of correctly predicting the grade of particular trees, although the percentage improvement over proportional, or naive, approaches for some species groups was small.

The estimated equations could be useful for incorporating tree grade into stand-level optimization models (e.g., those of Buongiomo *et al.* (1994, 1995), Haight *et al.* 1992), enabling more precise predictions of the economic implications of alternative management strategies Further, differing parameter estimates across species groups indicate that different stand structures and species mixes imply different product outputs.

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Methods

The Model

Standing sawtimber of all species in the eastern United States is graded in the periodic forest surveys conducted by the USDA Forest Service, using the following criteria (Hansen *et* al. 1992): trees are graded using the methods described in Schroeder *et* al. **(1968),** Brisbin and Sonderman **(1971),** and Hanks **(1976),** applying grades of **1, 2,** or 3 to the 16-foot butt logs of sawtimber trees. These models were developed in order to more accurately predict the grades of lumber and logs obtainable from trees, based on tree characteristics. A grade of 4 in the Forest Service's **Eastwide** Database, which was used in this study, was assigned to **sawtimber-size** trees that contained a gradeable butt log but did not meet grade 3 standards, and a grade of **5** was given to trees of sawtimber size that did not contain a gradeable butt log (Hansen et *al.* 1992). In FIA, all softwoods with a **9-inch** minimum diameter can be assigned grades, l-3, according to Schroeder *et al.* **(1968),** and Brisbin and Sonderman (197 1). Hardwood trees are graded according to rules developed by Hanks (1976): grade 1 trees must have a dbh (diameter at breast height) of 16 inches or greater; grade 2 trees must have a dbh of 13 inches or greater, and grade 3 trees must meet the minimum grading dbh of 11 inches. Grade 4 and 5 trees have only the minimum (1 l-inch) diameter requirement. Generally, the higher the number of clear faces in the **first** M-foot log, the higher the tree grade, with degrades for factors that cause a departure from a clear, straight bole.

Little published work exists regarding the relationship between tree grade and inventory variables **One** study, **Kärkkäinen** and Uusvaara **(1982),** examined the factors affecting the quality of young **Scots** pine **(*Pinus sylvestris*)** in Finland and found significant relationships to diameter and tree growth rate.

Because species vary widely in their tendency to self-prune and in their form, susceptibility to pathogens and to damage from weather and to catastrophic events, it is important to model tree grade by species Within a species, branching and tree form are affected by self-pruning, which is closely related to the degree of competition among trees; therefore, branching should be related to stand density. **On** the other hand, competition tends to promote stresses that can lead to pathogen entry and susceptibility to mechanical damage (Smith 1962, Walker 1980). Smith (1962) states that the rate of self-pruning is "determined by the initial density of the stand and the vigor of the tree." Implicit in **this** statement is that tree grade should also be related to site quality.

In this research, I hypothesized that the combination of grading characteristics, diameter, straightness, length of clear bole, and amount of defect, were related to tree species, tree diameter, stand density, and site quality. While model fitness might be better if growth rate were included, most common inventory data do not include this among the list of stand or tree variables In this research, these three variables were measured by dbh in inches, basal area per acre in square feet, and site index in feet **(fifty** year base), respectively. That is, for a particular tree within a species group,

$$\textit{tree grade} = f(\textit{diameter}, \textit{stand density}, \textit{site quality}) \tag{1}$$

Important features of the dependent variable in (1) are that it is discrete and that it could be characterized as ordered **This** variable is discrete because it can only take on a limited number of integer values It could be considered as ordered because a grade 2 tree has fewer branches and is straighter and less defective than grade 3, and a grade 1 tree has even fewer branches **and is** straighter and less defective than grade 2. These features suggested the ordered **probit** model (see Greene 1990) as one possible method for estimating the relationship between grade and characteristics of the tree and the stand.

The ordered probit model requires the specification of a latent variable, y^*, which is related in some fashion to a set of right-hand-side variables contained in a vector x. The value of y^* determines the region of maximum frequency in the normal distribution of each grade. That is,

$$y^* = f(x,\beta) + \epsilon \tag{2}$$

and,

$$\begin{aligned} y&=1 \quad if \; y^* < 0, \\ y&=2 \quad if \; 0 \le y^* < \mu_1, \\ y&=3 \quad if \; \mu_1 \le y^* < \mu_2, \\ y&=4 \quad if \; y^* \ge \mu_2 \end{aligned} \tag{3}$$

The μ's in (3) are estimated along with the parameters, β, in equation (2). Assuming that the unexplained variations around grades are normally-distributed, we have:

$$\begin{aligned} Prob[y=1] &= \Phi(-\beta' x), \\ Prob[y=2] &= \Phi(\mu_1-\beta' x)-\Phi(-\beta' x), \\ Prob[y=3] &= \Phi(\mu_2-\beta' x)-\Phi(\mu_1-\beta' x), \\ Prob[y=4] &= 1-\Phi(\mu_2-\beta' x) \end{aligned} \tag{4}$$

and

$$0 < \mu_1 < \mu_2 \tag{5}$$

where Φ is the cumulative distribution function of the normal distribution.

In estimating equations such as those implied by (1) and (2), species were grouped as shown in Table 1. In order to allow some flexibility in the relationships between grade and the chosen explanatory variables, I estimated a quadratic functional form of the right-hand-side variables, including squares and interactions of variables The models assumed that the variance of regression of each species group's equation was heteroscedastic, that is, an exponentially linear function of dbh, basal area per acre, and site index. In some cases, too few observations and (or) too little variation in the dependent variable prevented convergence of estimates in iterative maximum likelihood estimation. This was a common situation for species groups with few observations and for hardwoods smaller than 16 inches dbh. In these situations, quadratic terms were not included, and homoscedastic covariance matrices were estimated

Equations specified for white pine were exactly as described above. For southern pines, no grade 4 trees were contained in the sample, and for the grouping "other softwoods," no grade 1 trees were

Table 1. Summary statistics for variables used in model estimation.

Species Group	Variable	Minimum	Maximum	Mean
a. Southern pine	DBH (inches)	9.0	28.5	12.2
(n=3,149)	BA/acre (ft^2)	8.0	240.0	106
	Site index (50).....	30	99	68
b. White pine	DBH (inches)	9.0	36.9	16.7
(n=1,352)	BA/acre (ft^2)	23	248	129
	Site index (50).....	30	99	77
c. Hemlock	DBH (inches)......	9.0	43.8	17.5
(n=349)	BA/acre (ft^2)	8	240	133
	Site index (50)	40	99	76
d Other softwood	DBH (inches)......	9.0	16.3	11.8
(n=43)	BA/acre (ft^2)	15	188	108
	Site index (50)	50	99	62
e. Select white oak	DBH (inches)......	11.0	49.5	16.7
(n= 1,562)	BA/acre (ft^2)	8	240	103
	Site index (50)	40	99	69
f. Select red oak	DBH (inches)	11.0	51.1	18.9
(n=1,578)	BA/acre (ft^2)	15	218	115
	Site index (50)	30	99	71
g. Other oak	DBH (inches)......	11.0	52.7	16.5
(n=4,906)	BA/acre (ft^2)	8	225	105
	Site index (50)	30	99	67
h Soft maple	DBH (inches)......	11.0	35.9	15.0
(n=833)	BA/acre (ft^2)	8	225	111
	Site index (50)	40	99	75
i. Yellow-poplar	DBH (inches)	11.0	37.0	16.4
(n=2,685)	BA/acre (ft^2)	8	240	120
	Site index (50)	40	99	85
j. Other hardwood	DBH (inches)	11.0	40.6	16.1
(n=3,054)	BA/acre (ft^2)	8	240	111
	Site index (50)	40	99	76

contained in the sample. Further, for hardwoods, grading rules state that trees greater than or equal to 13 inches but less than 16 inches dbh could not be classed as grades 1. For these species groupings, slightly abbreviated forms of equations (2)-(5) were used, each of which allowed only three possible grades Finally, for hardwoods greater than or equal to 11 inches but less than 13 inches dbh, grading rules allowed no grade 1 or grade 2 classifications. In these cases, a simple binary choice (probit) model applied, with the choice being either a grade 3 tree or a grade 4 tree.

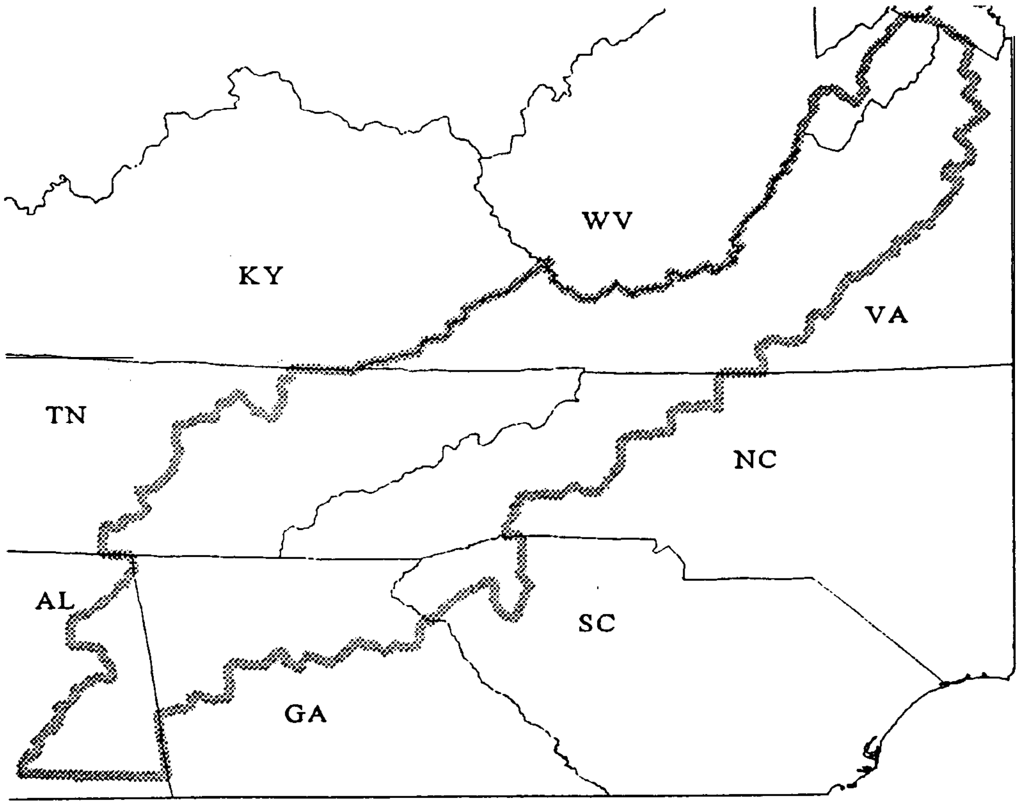

Figure 1. The Southern Appalachian Assessment Region.

Data

The data used (Table 1) to estimate these equations were derived from tree and plot records gathered from the southern Appalachians (see Figure 1) during state FIA surveys of 1986-1992. No distinction was made by ownership of the land where trees were sampled. Only trees that were graded and had complete data on dbh and associated plots with measured basal area and site index were used. As well, residual trees growing on plots that had been cut since the previous FIA survey were not included in the estimation, because these sites could have had basal areas that were substantially lower than the basal area prevalent during the development of the graded tree, and no old basal area data were available in the Eastwide database. Overall, 19,511 tree records and 2,722 associated plot records were used.

Methodological Issues

Important issues considered when modeling tree grade included the selection of explanatory variables, initial hypotheses as to how these variables are related to tree grade, and how to measure modeling success. In selecting explanatory variables, I considered standard theory in forest management (see Smith (1962) and Davis (1966)). In general, because tree grade is measured according to tree form, diameter, branchiness, and defect, it is reasonable to assume that factors affecting these variables would adequately explain tree grades Diameter is a limiting factor in determining grade. It is widely accepted that stand density plays an important role in encouraging many species of trees to self-prune. If site index causes a faster growth rate, then, given self-pruning, the faster that a tree grows, the more quickly it can overcome the effects of externally-caused mechanical damage and the more quickly it can grow over branch stubs

Each of the selected variables may have ambiguous effects on tree grade, however:

(i) While diameter is probably positively related to the length of clear bole and the number of clear faces on a stem, as a tree ages (gets larger), there is a greater chance that it has been subjected to pathogenic damage and other kinds of random mechanical damage during its life.

(ii) Although denser stands promote self-pruning and etiolation, the denser the stand, the greater the potential for stress from competition and the greater the likelihood that pathogens are passed from tree to tree.

(iii) Even if stand and tree vigor are related to site quality and thus to site index, site index is measured by FIA by taking the height of the three tallest dominant or codominant trees and comparing them with their ages. This measure might not correspond directly with tree vigor or even the species in question. For example, if a particular tree was not part of this site index measurement, it might have been among the trees in a stand that have been suppressed by the taller trees; such a suppressed tree might have stem form and other characteristics that cause a lower quality tree grade. Further, the height of, say, the tallest yellow-poplars in a stand may not correlate well with the heights of associated species or may in fact correlate negatively with them.

Functional form is determined by the dependent variable and by hypothesized relationships between it and explanatory variables. Considering the conflicting forces associated with each of the selected explanatory variables, the quadratic form should capture U-shaped and inverse-U-shaped relationships

Many measures of data fitness to discrete dependent variable models have been developed (see Maddala (1983), Judge *et al.* (1985), and Greene (1990) for descriptions of a few). An obvious and common measure is the percentage of correct predictions. This can be compared to the percentage of correct predictions obtained using some naive model (e.g., sample proportion for each grade). Combining these two, we have the increase in absolute percentage of correct predictions Gall this the fitness improvement index (FII):

$$FII = 100 \times \frac{(C_m - C_0)}{C_0} \tag{6}$$

where C_m is the number of correct predictions obtained using the estimated model and C_0 is the number of correct predictions assuming sample proportions.

Other measures of success in maximum likelihood involve likelihood criteria. One is the likelihood ratio test, with the criterion distributed chi-squared (k-l). This essentially tells whether the right-hand-side variables significantly explain any variation:

$$X^2 = -2(\ln L_0 - \ln \hat{L}) \tag{7}$$

where $\hat{L}$ is the log-likelihood of the estimated equation and L_0 is the log-likelihood of a model with only the intercept on the right-hand-side. Another criterion for model success is the likelihood ratio

index (Greene 1990):

$$LRI = 1 - \frac{\ln \hat{L}}{\ln L_0} \tag{8}$$

This is analogous to the R^2 of OLS, being bounded between zero and one, with higher values meaning a better fit of the data to the predicted values.

Often, maximum likelihood ordered **probit** model appears to predict in a biased fashion, with some categories of the dependent variable correctly predicted with much higher frequency than others. Maximum **likelihood** estimation maximizes the joint density of the observed dependent variables and not some fitting criterion, as in least squares. **Thus,** successful prediction rates may vary greatly among the different levels of the dependent variable. For example, if most trees are grade 3, then the estimated model may predict grade 3 trees well but other grades poorly. This means that the estimated model may have limited usefulness if one modeling objective were success in predicting, say, grade 1 trees

Results

Equation Estimates

Estimation results are presented in Tables **2-4.** Table 2 reports estimates for all softwood categories and hardwood categories for trees greater than or equal to 16 inches dbh. **Only** a subset of the **equations'** coefficients were statistically **significant** in explaining variation in tree grades In all models where a full quadratic specification was possible, at least one squared or interaction term was statistically different from **zero** at **5** percent significance. **That is,** it appears that the relationship between the stand- and tree-level variables with tree grade was more complex than a simple linear model. Linear terms were fairly **consistently significantly** different from zero, with diameter and basal **area** usually negatively signed, and with site index taking either positive or negative signs, depending on the species group. Note that a negative coeffkient means that an **increase** in an explanatory variable correlated with a decrease in tree grade number (i.e., higher tree quality). For models of smaller-diameter hardwood trees, most explanatory variables were statistically significantly related to tree grade, though the magnitudes and signs of the estimated coefficients revealed significant differences among species groups

Model Fitness

Tables 5-8 summarize predictive success of the estimated models Log-ratio indices showed generally low predictive power, with indices mainly less than 0.10. But log ratio tests, measured using a criterion distributed chi-squared, showed that the chosen explanatory variables did **significantly** explain grades, illustrating why it might be misleading to rely on one measure to evaluate success. Only a few estimated equations had statistically insignificant log ratio tests Models usually had a correct prediction rate of between 50 and 75 percent. As Table 8 shows, grade 3 trees, the most common tree grade for all species groups, were most accurately predicted. A majority of models were not as accurate in identifying trees of grades **1, 2** or 4. These grades were usually not detected and were thus lumped in with the truly **grade** 3; the result was over-prediction of the proportion of trees in grade 3 Tables 5-7 reveal that the percentage increase in **successful** predictions over a naive (proportional) model was around 10 percent.

Table 2. Estimated quadratic ordered **probit** models for prediction of tree grades for softwoods and hardwoods of dbh ≥ 16 inches in the Southern Appalachian mountains.'

Species Group	Int.	D	BA	SI	D^2	BA^2	SI^2	D*BA	D*SI	BA*SI	μ_1	μ_2
a. Soutbem pine .. (n-3,149)	4.68 (1.32) **	-0.13 (0.09)	-3.58e-3 (6.76e-3)	-4.96e-2 (2.45e-2) *	6.50e-3 (3.03e-3) *	4.56e-5 (2.47e-5)	7.30e-4 (2.78e-4) **	-2.37e-4 (3.63e-4)	-1.98e-3 (1.16e-3)	-1.06e-4 (8.90e-5)	0.91 (0.26) **	–
b. **White pine** .... (n= 1,352)	6.28 (1.97) **	-0.29 (0.093) **	-3.43e-2 (1.1Oe-2) **	3.27e-2 (2.82e-2)	4.73e-3 (1.77e-3) **	5.71e-5 (2.75e-5)	-2.29e-4 (2.02e-4)	6.50e-4 (2.86e-4)	-6.99e-4 (7.03e-4)	8.26e-5 (1.07e-4)	1.64 (0.36) **	5.321 (1.066) **
c. Hemlock ...... (n=349)	11.71 (4.40) *	-0.334 (0.133) *	-1.27e-2 (7.30e-3)	2.35e-2 (1.72e-2)							0.88 (0.22) **	2.07 (0.52) **
d. **Other softwood** . (n=43)	31.28 (100.5)	-0.925 (3.30)	-0.013 (0157)	-0.113 (0.46 1)							21.57 (59.61)	
e. Select **white** oak (n-733)	1.29 (0.43) **	8.51e-3 (8.97e-2)	(8.97e-2) (1.08e-3)	-1.07e-2 (3.81e-3) **							0.88 (0.84) **	9.32 (1.76) **
f. Select red **oak**.. (n=1,013)	7.97 (2.58) **	-3.1 le2 (1.07e-1)	-2.50e-2 (1.29e-2) *	-1.18e-1 (3.70e-2) **	2.10e-3 (1.82e-3)	4.81e-5 (4.13e-5)	5.43e-4 (2.14e-4) •	-4.68e-4 (4.04e-3)	-6.87e-3 (7.62e-3)	2.98e-4 (1.30e-4) *	1.63 (0.4 1) **	3.71 (0.91) **
g. **Other oak** ..... (n=2,254)	6.61 (2.01) **	-0.25 (0.11) *	8.95e-3 (1.18e-2)	-3.26e-2 (2.88e-2)	5.51e-3 (2.33e-3) •	-5.76e-5 (3.39e-5) **	2.52e-4 (1.78e-4)	2.26e-4 (4.17e-4)	-7.80e-4 (8.71e-4)	-6.24e-5 (1.05e-4)	2.06 (0.30) • *	4.83 (0.68) **
h Soft maple .... (n-257)	2.07 (0.62) **	0.016 (0.024)	-3.52e-3 (1.86e-3)	-4.12e-3 (4.66e-3)							1.14 (0.14) **	2.60 (0.16) **
i. Yellow-poplar .. (n-1.274)	2.73 (1.07) *	-5.20e-2 (2.64e-2) •	-2.39e-3 (1.76e-3)	-9.78e-2 (5.52e-3)							1.72 (0.56) **	3.73 (1.22) **
j. **Other hardwood** . (n= 1,270)	8.11 (3.70) •	-0.14 (0.18)	1.33e-3 (1.36e-2)	-9.73e-2 (5.21e-2)	-2.87e-4 (3.13e-3)	4.15e-5 (3.57e-5)	6.90e-4 (2.86e-4)	6.43e-4 (5.68e-4)	4.80e-3 (1.39e-3) **	-3.34e-4 (1.47e-4) *	1.87 (0.44) **	4.21 (1.02) **

'D=Diameter; BA=Basal area per acre, in square feet; SI=Site index, 50 year basis. Two asterisks indicate significance at 1%, one asterisk 5%.

Table 3. **Estimated** ordered **probit** models for prediction of tree grades for hardwoods of dbh greater than or equal to 13 inches and less than 16 inches in the Southern Appalachian mountains.[1]

Species Group	**Int.**	D	BA	**SI**	μ_1
a. Selectwhiteoak . . . . (n-499)	63.19 (57.83)	-3.91 (3.60)	**-3.61e-2 (3.95e-2)**	**2.85e-3 (5.95e-2)**	20.20 (17.51)
b . **Select red oak.** . . . . . (n-337)	5.70 (1.14) **	0.33 (0.08) **	**-1.63e-3 (2.17e-3)**	**-9.32e-3 (4.87e-3)**	2.11 (0.15) **
c. **Other oak** . . . . **(n-1,502)**	30.46 (15.96) *	-1.46 (0.80)	**-2.42e-2 (1.43e-2)**	**-3.94e-2 (2.50e-2)**	13.05 (6.40) *
d. **Soft maple** . . . . (n-278)	2.49 (1.23) *	-7.7 **1e-2 (8.17e-2)**	**-4.79e-3 (2.32e-3)** *	**1.70e-3** (5 **.40e-3)**	1.82 (0.11) **
e. Yellow-poplar . . . . . . (n-882)	4.11 (0.75)	-0.25 (0.05) **	**-1.31e-2 (1.26e-2)**	**-4.57e-3 (3.71e-3)**	1.58 (0.07) **
f. other hardwood . . . . . **(n-1,001)**	26.25 (17.00)	-1.37 (0.91)	**-1.26e-3 (1.01e-2)**	**-1.66e-2 (2.21e-2)**	11.35 (6.88)

[1] D-Diameter; BA-Basal area **per** acre, in **square** feet; SI-Site index, 50 year basis. Two asterisks indicate statistical **significance** at **1%,** one asterisk 5%.

Table 4. Estimated **probit** models for prediction of tree grades for hardwoods of dbh greater than or equal to 11 inches and less than 13 inches in the Southern Appalachian mountains[1]

Species Group	**Int.**	D	BA	**SI**
a **Select white oak** . . . . (n-330)	**1.02 (24.99)**	**-0.10 (2.30)**	**3.52e-3 (3.45e-2)**	**-2.25e-2 (2.36e-1)**
b. Selectredoak . . . . . . (n-228)	**-0.04 (2.55)**	**-9.60e-2 (2.10e-1)**	**-3.85e-3 (3.93e-3)**	**-3.55e-3 (8.80e-3)**
c. **Other oak** . . . . **(n-1,150)**	1.71 (0-94)	-1.17 (0.08) •	**-5.17e-3 (1.54e-3)** • *	**-4.07e-4 (3.24e-3)**
d. Softmaple . . . . **(n-298)**	1.40 (1.82)	-0.19 (0.15)	**-1.54e-3 (2.42e-3)**	**2.35e-3 (6.12e-3)**
e. Yellow-poplar . . . . . . (n-579)	0.09 (1.57)	**-8.56e-2 (1.30e-1)**	**- 1.67e-3 (2.12e-3)**	**-2.45e-3 (6.48e-3)**
f. Other hardwood . . . . . (n-783)	931 (28.68)	-1.39 (3.73)	**-5.15e-2 (1.15e-1)**	0.10 (0.22)

[1] **D-Diameter; BA-Basal** area **per** am. in square feet; **SI-Site index,** 50 **year basis. Two** asterisks **indicate** statistical significance at **1%,** one asterisk 5%.

Table 5. Goodness of fit measures for estimated species group models, dbh ≥ 16 inches

Species Group	Log-Patio Index	chi-squared	Percent Correct Predictions	Fit Improvement Index
a. Southern pine . . . (n=3,149)	0.04	174**	74.7	15.2
b. White pine ..... (n= 1,352)	0.08	205**	59.0	12.7
c. Hemlock. ...... (n=349)	0.15	105*	63.0	17.6
d Other softwood .. (n=43)	0.18	8	86.1	11.0
e. Select white oak . (n=733)	0.01	23	44.3	13.0
f. Selectredoak... (n=1,013)	0.03	79**	42.5	9.7
g. Other oak . . . . . . (n=2,254)	0.02	112**	43.2	10.1
h Soft maple . . . . . (n=256)	0.02	9	52.3	15.3
i. Yellow-poplar ... (n= 1,274)	0.01	20*	41.3	8.3
j. Other hardwood . (n=1,270)	0.02	70**	42.8	10.1

There are several possible explanations for why these models were only modestly better than proportional models in predicting tree grades Probably very important was the omission of variables describing genetics and stand histories. Genetic factors, aside from interspecies variations, are not easy to model. Stand history variables were omitted, even though some were available from FIA. But one of the goals of this research was to use commonly-gathered inventory data to help predict tree grades

Conclusions

Tree grades are based upon the grades of logs and lumber obtained upon harvest and wood product manufacture. If more successful models of tree grades can be estimated, then more precise estimates of stand values by grade can be developed Results of tree grade model estimation presented here for southern Appalachian trees and associated stands indicate that tree grades can be statistically significantly predicted Estimation revealed important differences among species, so it is important to recognize species when modeling tree grade. Model form was adequately explained using a linear right-hand-side functional form of explanatory variables, although some species groups showed more complex, nonlinear relationships. While the explanatory powers of estimated models were not high, research uncovered statistically significant relationships between tree quality and diameter, basal area, and site index. Several model fitness criteria were used to evaluate the success of this modeling, and,

Table 6. Goodness of fit measures for estimated species group models, 13 ≤ dbh < 16 inches.

Species Group	Log-Ratio Index	chi-squared	Percent Correct Predictions	Fit Improvement Index
a. Select white oak . (n=499)	0.04	**37****	57.7	15.9
b. Select red oak ... (n=337)	0.08	**41****	63.2	15.6
c. Other oak ...... (n=1,502)	0.03	**69****	61.2	14.9
d Soft maple ..... (n=278)	0.01	6	63.0	16.4
e. Yellow-poplar ... (n=832)	0.02	**33****	56.4	12.0
f. Other hardwood . . (n=1,001)	0.02	**39****	58.4	14.5

Table 7. Goodness of fit measures for estimated species group models, 11 ≤ dbh < 13 inches.

Species Group	Log-Ratio Index	chi-squared	Percent Correct Predictions	Fit Improvement Index
a. Select white oak . (n=330)	0.02	8	80.9	11.8
b. Select red oak ... (n=228)	0.01	1	91.2	7.2
c. Other oak ...... (n=1,150)	0.02	**17****	81.7	11.6
d Soft maple ..... (n=298)	0.01	2	78.9	12.2
e. Yellow-poplar . . . (n=579)	0.00	2	90.7	7.6
f. Other hardwood . . (n=783)	0.02	**16***	82.1	11.8

Table 8. Percentage of individual softwood trees at least 9 inches dbh and hardwood trees at least 11 inches dbh with correctly predicted tree grades, based on the models shown in Tables 2-4, versus naive predictions of grades.

Species Group	Predictor	Grade 1	Grade 2	Grade 3	Grade 4	All Grades
a. Southern Pines	Models . . .	0.0	0.0	100.0	NA	74.7
(n=3,149)	Naive	7.6	17.7	74.7	NA	59.5
	Difference .	-7.6	-17.7	25.3	NA	15.2
b. White Pine	Models . . .	0.0	4.4	95.5	0.0	59.0
(n=1,352)	Naive	8.7	30.1	60.4	0.7	46.3
	Difference .	-8.7	-25.7	35.0	-0.7	12.7
c. Hemlock	Models . . .	34.3	10.0	91.7	0.0	63.0
(n=349)	Naive	10.0	22.9	62.5	4.6	45.5
	Difference .	24.3	-12.9	29.3	-4.6	17.5
d Other Softwoods	Models . . .	NA	0.0	100.0	0.0	86.0
(n=43)	Naive	NA	7.0	86.0	7.0	75.0
	Difference .	NA	-7.0	14.0	-7.0	11.0
e. Select White Oak	Models . . .	0.0	49.9	82.0	0.0	56.3
(n-1,562)	Naive	19.8	34.9	57.3	13.3	42.7
	Difference .	-19.8	15.0	24.8	-13.3	13.7
f. Select Red Oak	Models . . .	21.9	73.0	56.7	0.0	53.9
(n=1,578)	Naive	28.8	41.4	54.6	4.9	43.3
	Difference .	-6.9	31.6	2.0	-4.9	10.6
g. Other Oaks	Models . . .	2.8	7.8	96.3	0.0	57.7
(n=4,906)	Naive	14.0	31.6	61.9	13.0	45.8
	Difference .	-11.2	-23.9	34.4	-13.0	11.9
h Soft Maples	Models . . .	0.0	0.0	100.0	0.0	65.4
(n=832)	Naive	5.1	21.6	67.2	20.0	50.8
	Difference .	-5.1	-21.6	32.8	-20.0	14.5
i. Yellow-Poplar	Models . . .	45.9	65.6	61.0	0.0	56.6
(n=2,685)	Naive	36.4	43.4	59.7	6.6	47.3
	Difference .	9.5	22.2	1.3	-6.6	9.3
j. Other Hardwoods	Models . . .	4.4	4.5	97.3	1.0	58.0
(n=3,054)	Naive	14.3	31.3	62.2	13.0	46.0
	Difference .	-9.9	-26.7	35.1	-12.8	12.0

in my opinion, significant improvements in tree grade estimation success were attained This success may have implications for timber supply and stand optimization modeling.

Nonetheless, modeling left unexplained a large proportion of variation in tree grades, and substantial apparent bias was associated with the models. The estimated equations were only modestly better than proportional, or naive, models in predicting tree grades, and this was probably because of omitted variables, possibly stand history and genetic factors The biases of these models, that grade 3 trees were over-predicted and that other grades were under-predicted, might have been expected from maximum likelihood estimation, given its maximization criterion. Constraining the maximum likelihood model to better predict less common grades would inevitably result in poor model prediction success as measured by the fitness criteria that we described. However, perhaps some value-weighted model, which put more weight on correctly predicting much higher-value number 1 and 2 grade trees, could be more successful if fitness were viewed from a financial or economic perspective.

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